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RETURNS TO AMERICAN AGRICULTURAL RESEARCH: ARE WE ASSESSING RIGHT?

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ABSTRACT

This study assesses the returns to American agricultural research investments for the years 1930 through 1990 using an error correction model. The estimated internal rates of return are 27% for public research and 6% for private research. These estimates from the most comprehensive and timely data assembled to date indicate that returns to public agricultural research compare favorably to real returns on alternative long-run investments, but do not call for large increases in investments suggested by previous studies or for the drop in public research expenditures appropriated by the United States congress in recent years.

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Much of the technological success of American agriculture is attributable to a well developed and highly effective system of public and private research and education. This system includes basic and applied research along with extension education. Investments in research and extension have been a primary source of US agricultural multifactor productivity growth that averaged 2 percent per annum from 1930 to 1990. During this same period public and private investment in agricultural research grew at an annual rate of 3 and 4 percent, respectively. In 1990, the nation spent about $8 billion dollars on agriculture research and extension, 45% of which was financed by the public and the rest (55%) by the private sector (Figures 1 and 2).

In recent years, public expenditures on agricultural research and extension have come under increasing scrutiny. Large U.S. federal budget deficits have resulted in proposals to reduce expenditures for agricultural research and extension. Before reducing publicly funded agricultural research and extension investment, policy makers need to understand the long-term benefits from these investments.

Numerous studies have reported favorable payoffs from research and extension investments made to increase agricultural productivity. Huffman and Evenson (1993), for example, report an internal rate of return (IRR) of 41% for public research and 46% for private R&D. Makki and Tweeten, on the other hand, report a higher IRR to public research and extension (93%) compared to private R&D (45%). Yee reports rates of return to public research ranging from 40 to 58% depending on assumptions regarding the omission of private R&D and deadweight loss created by taxation[1]. Other studies estimate IRRs ranging up to 300% (Braha and Tweeten; Chavas and Cox; Cline; Davis; Griliches; Huffman and Evenson, 1989; Knutson and Tweeten)[2].

Two observations follow regarding these reported rates of return. First, most are quite high and exceed observed market rates of return on alternative investments. one useful comparison is from Malkeil who, after an extensive review of the financial literature, concluded that the rate of return on long-term assets in the U.S. is about 10 percent. Second, the wide disparity among IRR estimates raises questions regarding the sensitivity of these estimates to the use of different time periods and methodologies. Time series regression analyses have been widely used to measure impacts of R&D on agricultural productivity (Cline; Huffman and Evenson 1992 and 1993; Griliches; Makki and Tweeten; Yee). These studies have helped to identify the dynamics of payoffs from investments in developing technology and infrastructure. Inferential dangers arise, however, in directly applying time series regression analysis to estimate economic benefits when variables have strong trends and are nonstationary as is typical for the data series used in IRR analysis. Regression models estimated from nonstationary series frequently have high R^2 statistics, highly significant coefficient estimates, and very low Durbin-Watson (DW) statistics (Granger and Newbold; Makki and Tweeten; Yee). In such situations the usual statistical tests of regression coefficients can be seriously biased towards accepting a

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[1] These studies differ in their methods of estimation and the chosen time period: Huffman and Evenson (1993) uses Zellner's Seemingly Unrelated Regression (SUR) method for years 1950 through 1982, while the Makki and Tweeten and Yee adopt the polynomial distributed lag (PDL) technique for the periods 1930-1990 and 1931-1985, respectively.

[2] Chavas and Cox, using an alternative non-parametric methodology, report positive, yet substantially lower IRRs of 28% and 17% respectively for public and private research investments using data for 1950 to 1982. Although the nonparametric approach has some advantages over a parametric approach, the major limitation is that statistical testing of the reliability of parameter estimates is not possible (see Chavas and Cox for details).

spurious relationship. Furthermore, the marginal rate of return derived from such a relationship can overestimate the actual returns from research investments.

Cointegration analysis can improve estimates of the long-run dynamic relationship among time series economic variables which are nonstationary and show strong trends (Engle and Granger). The cointegration concept brings together short-run and long-run information in modeling time series data via an error correction model ECM (Ericsson; Perman).

This paper reports the results and conclusions of an analysis implementing the cointegration technique to measure the influence of public research and extension and of private research and development on U.S agricultural productivity. Our analysis improves estimates of the IRR for public and private research investments in U.S. agriculture by appropriately accounting for the trend and nonstationarity inherent in time series data on agriculture productivity and public and private research investments. In addition, our results estimate the contribution of education, government commodity programs, and terms of trade to U.S. agricultural productivity.

The paper is organized as follows. The first section provides a discussion of the data used in the study and the selection of variables. The second section presents the econometric procedures to test data nonstationarity and cointegration and to estimate an error correction model. The third section contains the empirical results. The final section provides the conclusions of the study.

Productivity Model

Aggregate measures of U.S. agricultural productivity have been well developed and widely used in the literature (Huffman and Evenson 1989,1992,1993; Makki and Tweeten, Yee).

The most commonly used measure of agricultural productivity is a ratio of *aggregate crop and livestock output* to *aggregate production inputs*. Agricultural productivity is influenced by various factors. The more important ones are (i) past and present public and private research investments in improving technology and infrastructure, (ii) education level of farm operators, (iii) government commodity programs, (iv) terms of trade faced by producers, and (v) the weather[3].

Conceptually, multifactor productivity (MFP) of agriculture can be specified as

$$(1) \qquad MFP_t = \alpha_0 + \sum_{j=0}^{m} \alpha_{1j}\, PRE_{t-j} + \sum_{j=0}^{m} \alpha_{2j}\, PRD_{t-j} + \alpha_3 EDU_t + \alpha_4 FTT_t + \alpha_5 EPC + \alpha_6 WRF_t + e_t$$

where variables are defined in Table 1 along with their source. All variables are annual data for the United States from 1930 through 1990. Public research and extension (PRE), private research and development (PRD), farm operator education (EDU), and weather (WRF) variables frequently have been used to account for multifactor productivity and need little elaboration (Braha and Tweeten; Chavas and Cox; Cline; Huffman and Evenson 1992, 1993; Griliches; Knutson and Tweeten; Makki and Tweeten; Schimmelpfennig and Thirtle; Yee). We combine research and extension because they are strong complements whose separate contributions are not easily sorted out.

The variables factor terms of trade (FTT) and government commodity programs ordinarily are not used to explain agricultural productivity and hence require some elaboration.

[3] Weather is an important variable in cross sectional productivity analysis, but may not be as important in the long-run time series analysis of agricultural productivity. We provide evidence for this argument elsewhere in the paper.

Table 1. Data Source and Variables: 1930-1990

Variable Name	Variable Definition
MFP	Multifactor productivity index is the ratio of *aggregate crop and livestock output* to *aggregate production inputs*, 1990 = 100 (U.S. Department of Agriculture, May 1992 and earlier issues).
PRE	Research and extension real outlays by land-grant universities, the U.S. Department of Agriculture, state agricultural experiment stations, and Cooperative Extension Service, in million 1990 (constant) dollars (Huffman and Evenson, 1993; USDA publications).
PRD	Private investment in research and development by private industries, foundations, etc., in millions of 1990 (constant) dollars (compiled from a variety of published sources including Huffman and Evenson, 1993; and USDA publications).
EDU	Education level of farm operators measured in terms of number of years of schooling. Data until 1972 are from Cline (p. 141) and for later years from Bellamy. Because data from Bellamy were compiled from the Census of Agriculture and Current Population Reports of the U.S. Census and were not available for every year, we interpolated between years.
CTT	Commodity terms of trade, defined as the ratio of the index of prices received for all crops and livestock to the index of prices paid for all production inputs (Council of Economic Advisors, various issues).
FTT	Factor terms of trade, defined as real prices received by farmers for commodities per unit of production inputs (Council of Economic Advisors, various issues).
EPC	Excess production capacity defined as output diverted from the market by acreage diversion, stock accumulation, and subsidized exports, expressed as a percent of farm output (Dvoskin; updated to 1990 using Dvoskin's procedure).
WRF	Weather related factors, measuring the impact of nature (precipitation, temperature, etc.) on farming, and calculated by Stallings from annual yield changes on experimental yield plots across the nation treated similarly except the weather, extended by Cline to 1972. Data were extended to 1990 by the authors using deviations of U.S. crop yields from a 7-year centered moving average yield trend.

Factor terms of trade may influence productivity if an improved overall economic climate encourages substitution of improved capital inputs for less productive conventional inputs such as labor. A favorable economic climate also can generate cash flow and loosen capital budget constraints.

We use factor terms of trade, defined as real prices received for commodities per unit of aggregate input, rather than commodity terms of trade (CTT) to measure aggregate economic climate[4]. Because commodity terms of trade is FTT/MFP, inclusion of CTT as an explanatory variable introduces specification error because MFP appears on both sides of the equation. Thus FTT is commodity terms of trade corrected for productivity. FTT has increased over time while CTT has substantially declined. Higher levels of FTT indicate greater incentives to add farming resources, some of which may be highly productive. Thus FTT is intuitively and conceptually more appealing than CTT as a measure of incentives for induced technological innovations (Hayami and Ruttan). The maintained hypothesis is that favorable factor terms of trade raise farm productivity.

Government commodity programs potentially can have various impacts on productivity. First, government programs can distort allocation of resources and products, reducing productivity. Second, programs provide payments that, if decoupled, might loosen budget constraints and provide funds allowing producers to substitute technologically improved inputs

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[4] In 1963, Heady and Tweeten (p. 447) found no statistically significant association between multifactor productivity and commodity terms of trade defined as the ratio of *the prices received for all crops and livestock* P_q to *the prices paid for all production inputs* P_x. It is surprising that a negative association was not found. Because productivity is aggregate output Q divided by aggregate input X, in economic equilibrium $P_qQ=P_xX$ so that $Q/X=P_x/P_q$. Thus commodity terms of trade defined as P_q/P_x will fall proportional to productivity gains Q/X. Use of wrong price variable in statistical analysis over time will give the incorrect impression that lower terms of trade raise productivity.

for conventional inputs, raising productivity. Third, in constructing MFP, analysts include diverted acres in production inputs. However, neither displaced output nor government payments are included in output, hence acreage diversion programs can be expected to reduce productivity. Slippage is great, however, as poor land is diverted and commercial fertilizers and other improved inputs are substituted for land. Given this conflicting conceptual foundation, the issue of whether commodity programs enhance or diminish productivity must be resolved empirically. Each of the above three potential impacts cannot be clearly isolated, but we considered three variables measuring the influence of commodity programs : excess production capacity, payments to farmers, and diverted acres. Excess production capacity (EPC) was deemed to be the most comprehensive measure of government distortion, and we included it in our model. Our null hypothesis is that government commodity programs as measured by EPC have no net impact on multifactor productivity.

Methodology

Cointegration analysis, introduced by Engle and Granger, provides a structural framework for quantifying and statistically testing long-run relationships among economic variables. Cointegration essentially links the long-run (steady state) behavior of economic time series to a statistical modeling of those variables. The concepts of cointegration and error correction modeling are closely related. As defined by Engle and Granger, two variables are cointegrated if each variable individually is stationary in differences (integrated of order d), and some linear combination of them is stationary in levels[5]. Cointegration implies that deviations

[5] An economic time series like MFP_t is stationary if its mean, variance and autocovariances are invariant with respect to time and the series is said to be integrated of order **d** or I(d) if it becomes stationary after differencing **d** times.

from equilibrium are stationary, with finite variance, even though the series themselves are non-stationary and have infinite variance. Engle and Granger establish that two cointegrated variables have an ECM representation, and two variables in an ECM representation must be cointegrated (this is called the Granger Representation theorem).

In practice, the cointegration approach involves three steps. The first step establishes that the series is nonstationary, or more specifically must be difference stationary[6]. The second step establishes whether the multivariate time series are cointegrated. If a cointegrating relationship is found, then the final step involves estimation of an error correction model.

Nonstationarity

Nonstationarity is investigated for each variable by testing for unit roots using Augmented Dickey-Fuller (ADF) statistics and Z-statistics, Z_α and Z_t (Phillips and Perron; Said and Dickey). These residual based tests are most often used by researchers due to their intuitive clarity and, more importantly, because they are more powerful than alternative non-residual based tests (J-test by Park and Choi; trace test; eigenvalue test), especially when the number of variables involved increases (Haug; Phillips and Ouliaris). The autocorrelation function (ACF) and partial autocorrelation function (PACF) also are used to substantiate the two tests, and to choose the order of differencing.

Consider, for example, the time series multifactor productivity index MFP_t. To test whether this series is nonstationary, we specify the following first order autoregressive model:

(2) $$MFP_t = \alpha + \beta * MFP_{t-1} + u_t , \qquad t=1,2,\ldots,T \cdot$$

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[6] If a nonstationary time series can be made stationary by differencing, then such a series is referred to as difference stationary data series.

The series is stationary only if $|\beta| < 1$. If $|\beta| = 1$, the series has a unit root implying nonstationarity. We test the null hypothesis of nonstationarity by reparameterizing (2) into a first difference equation:

(3) $$\Delta MFP_t = \rho * MFP_{t-1} + u_t,$$

which is nonstationary under the null $\rho=0$ (equivalent to $\beta=1$ in (2)).

In practice, a time trend (T) can be included in the estimated models to discriminate between unit root nonstationarity (Difference Stationary), and stationary about a deterministic trend (Trend Stationary). For example, Said and Dickey recommend the use of the Augmented Dickey-Fuller (ADF) regression of the following form:

(4) $$\Delta MFP_t = \alpha + \gamma * T + \rho * MFP_{t-1} + \sum_{i=1}^{m} \beta_i \Delta MFP_{t-i} + u_t.$$

Lagged first difference terms (**m** of them) are included in the model to ensure white-noise residuals in the regression of (4). The null hypothesis $\rho=0$ implies that MFP_t is nonstationary. The coefficient ρ is tested for statistical significance by comparing computed ADF τ-statistics with critical values. The null hypothesis of nonstationarity is rejected if the computed statistic is less than the appropriate critical value.

Dickey and Fuller note that the usual t and F tests are inappropriate for testing the null hypothesis of nonstationarity because the least squares estimate of β is not distributed around unity. They suggest ADF-t and ADF-F statistics as alternatives to the usual t and F tests. Phillips and Perron show that asymptotically the test statistics ADF and Z have similar limit distributions. However, the Z-test is preferred over the ADF-test for small samples because the former involves nonparametric adjustments to the time series structure to ensure that the random component is white noise. They also demonstrate that whenever uncertainty exists regarding the dynamic structure of the time series, the Z-test performs more consistently.

Cointegration

After verifying that the random variables are nonstationary as measured in levels, cointegration is investigated using four different statistics: ADF, Z, *p* (Phillips and Ouliaris), and SW (Stock and Watson). The existence of cointegration is tested in two stages. First, a cointegrating regression is estimated of the type

(5) $$MFP_t = \alpha + \beta * R_t + e_t,$$

where R_t is a vector of explanatory variables: PRE_t, PRD_t, EDU_t, FTT_t, EPC_t, and WRF_t. For variables to be cointegrated all the series should be integrated of the same order and a linear combination of the series should be stationary. Let $\hat{e}_t$ be the residuals estimated from (5). These residuals are used to test the null hypothesis of no cointegration, i.e., $\theta=0$, in either of the following specifications:

(6) ADF-t in the regression: $$\Delta\hat{e}_t = -\theta * \hat{e}_{t-1} + \sum_{i=1}^{m} \delta_i * \Delta\hat{e}_{t-i}\ , \quad \text{or}$$

(7) Z-test in the regression: $$\hat{e}_t = \theta * \hat{e}_{t-1} + u_t.$$

The null hypothesis of no cointegration is rejected if the appropriate test statistic is less than the critical value[7].

[7] See Phillips and Ouliaris for the construction and comparison of ADF, Z, and *p* statistics. SW statistics are illustrated in Stock and Watson.

Error Correction Model

Conditional upon finding evidence for cointegration, an ECM is specified as follows:

$$(8)\qquad \Delta MFP_t = A + \lambda \hat{e}_{t-1} + \sum_{j=0}^{m} \alpha_j \, \Delta PRE_{t-j} + \sum_{j=0}^{m} \beta_j \, \Delta PRD_{t-j} + \gamma_1 \, \Delta EDU_t + \gamma_2 \, \Delta FTT_t + \gamma_3 \, \Delta EPC_t + \gamma_4 \, \Delta WRF_t + u_t$$

where all variables are in first differences (indicated by Δ), $\hat{e}_{t-1}$ is the equilibrium error obtained from the cointegrating regression (5), A is the intercept, and u_t is the error term. The expression $\lambda\hat{e}_{t-1}$ in (8) contains valuable information on the long-run equilibrium properties of the time series variables, and it measures the extent to which actual data deviate from the long-run relationship among economic variables. The coefficient λ measures the speed with which the long-run relationship moves back to the equilibrium following a shock (λ needs to be negative for dynamic stability). All terms in (8) are integrated of order zero I(0), so that no inferential difficulties arise. Classical testing procedures, which are invalid under nonstationarity, are directly applicable to an ECM of cointegrated series.

The ECM model allows for lagged values of public and private research investments. Choosing a lag length that is too large or too small will reduce the predictive power of the model (Said and Dickey). An appropriate lag length **m** is chosen based on the commonly used Schwartz Criterion and Akaike Information Criterion (Judge et al.; Mills).

Consistent estimation of (8) can be achieved if there is no simultaneity between productivity and research investments. It is sometimes argued that in the above model research investment could be driving productivity and simultaneously productivity driving research, causing a fundamental identification problem. The Hausman specification test and Granger

Causality tests are performed to check the presence of simultaneity problem, if any (Granger; Pardey and Craig; Pindyck and Rubinfeld). The computation procedure is presented in Appendix B.

Empirical Results

Nonstationarity

Each variable in Table 1 was checked for nonstationarity by visual inspection of the estimated correlogram, a graph that plots the estimated kth order autocorrelation coefficient as a function of k, where k is the number of lags. For a stationary variable the correlogram should show autocorrelations that dampen fairly quickly as k becomes large. A smooth falling ACF suggests that the time series variable may be homogenous nonstationary, while a PACF with a cut off after the first lag suggests that the variable can be made stationary by differencing once (Mills; Kennedy). Based on these correlograms (figures 1 through 6) presented in Appendix A, we can say that all variables are first difference stationary.

The data nonstationarity is investigated also using the ADF test and the Z test. First, the variables are tested for the null hypothesis of I(1) or nonstationary against the alternative hypothesis of I(0) or stationary. The decision rule states that if the computed test statistic is more negative than the respective critical value reject the null hypothesis in favor of the alternative hypothesis. If the hypothesis of I(1) is not rejected, we need to test whether the series is I(2). This is accomplished using the same tests as before, but replacing the variable in levels by the variable in differences. The procedure is repeated until the order of integration of the series is established. The results reported in Table 2 support the hypothesis of data nonstationarity in almost every case. The hypotheses of I(0) or I(2) are rejected for all variables

Table 2. Testing for Data Nonstationarity[a]

Variable	Rho[b]	ADF-Test	CV	Z-Test[c]	CV
Levels					
MFP[d]	1.00	-2.8856	-3.89	1.3733	-13.87
PRE	0.59	-3.0281	-3.89	-24.5969	-26.01
PRD	0.80	-2.3379	-3.89	-11.6771	-26.01
EDU	0.86	-2.0919	-3.89	- 8.7266	-26.01
FTT	0.63	-2.9595	-3.89	-21.9930	-26.01
EPC	0.93	-1.8726	-3.89	-4.9976	-26.01
WRF[e]	-0.001	-4.2286	-3.89	-60.3735	-26.01
First Differences					
ΔMFP	-0.39	-8.7131	-3.89	-79.7004	-26.01
ΔPRE	-0.17	-4.2070	-3.89	-69.2269	-26.01
ΔPRD	-0.07	-5.8586	-3.89	-63.6373	-26.01
ΔEDU	0.11	-4.0233	-3.89	-52.1667	-26.01
ΔFTT	-0.19	-5.2837	-3.89	-70.0514	-26.01
ΔEPC	0.36	-5.2186	-3.89	-38.3232	-26.01

a. The algorithms given in *Gauss Procedures for Cointegrated Regression Models* are used for this purpose. Reject the null hypothesis of nonstationarity if the computed statistic is less than the critical value (CV).
b. Rho is the autoregressive parameter.
c. Two statistics, Z_α and Z_t, are associated with Phillips' and Perron's Z test. Both tests are performed for this study, but only Z_α is reported.
d. The ADF test for MFP rejects the null of nonstationarity at lower lags (< 2).
e. Both tests for WRF reject the null of nonstationarity at 5%.

except weather in favor of I(1). The weather variable therefore is dropped from the analysis since it cannot be cointegrated with agricultural productivity[8]. It can be concluded that the data used in the study were nonstationary in levels, and were stationary in first differences.

Cointegration

With strong evidence that each of our data series are nonstationary and integrated of the same order, we now proceed to test for cointegration. The cointegrating regression (5) is

[8] It is reasonable to assume that weather is a random phenomenon, and has no long-run relationship with agriculture productivity.

estimated with MFP as the dependent variable and PRE, PRD, EDU, FTT, and EPC as explanatory variables. The residuals from the regression are used to test for cointegration. Table 3 reports the results of cointegration tests, together with the associated critical values.

The test statistics uniformly indicate that the null hypothesis of *no cointegration* can be rejected. We conclude that the time series variables MFP, PRE, PRD, EDU, FTT, and EPC move in tandem. All tests computed with two year lags and a trend variable confirm the presence of cointegration at the 5% level of significance. The cointegration suggests existence of long-run relationships among these variables.

Table 3. Testing for Cointegration[a]

Test		Test Statistic	Critical Value[c]
ADF Test[b]	ADF-t	-5.12	-4.91
Z Test	Z_α	-56.17	-37.98
p Test	p_z	209.60	176.31
SW Test	SW	-29.92	-21.21

a. In the case of ADF, Z, and SW tests we reject the null of no cointegration if the estimated statistic is less than the critical value. In case of the *p*-test, where the p_z statistic possesses a nonstandard distribution, we reject the null hypothesis if the p_z statistic is greater than the critical values.
b. All tests provide consistent estimates of test statistics except the ADF test. The ADF test is biased toward accepting the null of no cointegration at higher lags (>3).
c. Critical values at 5% are taken from Phillips and Ouliaris.

Error Correction Model

Table 4 reports estimates of the error correction model (8). Both the Hausman specification test and Granger causality test suggest that the causality is unidirectional from R&D to productivity and not vice versa (Appendix B).

Table 4. Estimation Results of Error Correction Model, MFP Dependent[a].

Variable Name	Coefficients	t-Statistic	Productivity Elasticity
Public R&E[b]	0.0130	c	0.38
Private R&D[b]	0.0028	c	0.17
Farmers Education	0.3220	2.27	0.32
Terms of Trade	0.1609	2.18	
Excess Capacity	0.7089	0.72	
Error Correction	-0.8652	-3.53	
Constant	-0.1074	-0.13	
Adjusted R-Square:	0.82		
Durbin-Watson Statistic[d]:	1.95		
Schwartz Criterion	28.76		
Akaike Information Criterion	6.50		

a. Weather variable is not explicitly included in the cointegration model because the error correction term accounts for all random disturbances.
b. For public R&E and private R&D the aggregate value of coefficients is presented to save space.
c. The estimated Likelihood Ratio statistics for public R&E and private R&D were 64.56 and 70.08, respectively, with the corresponding critical values of 37.6 and 34.8 at the 1% level of significance.
d. The estimated first order autoregressive coefficient was 0.02.

A statistically significant negative error correction coefficient implies that the equilibrium relationship will hold in the long-run, even if there were shocks to the relationship. The error correction term measures the extent to which actual data deviate from the long-run relationships among the variables. In essence, it contains all the long-run information provided by levels data.

Choosing appropriate lag lengths is no easy task. Preliminary sensitivity analysis indicate that coefficients are quite stable for a wide range of lags. For example, the coefficients for education decreased from 0.35 to 0.28 when lags for private research were increased from 16 to 28, holding lags for public research at 20. The length of the available data precludes extending the sensitivity analysis beyond 28 lags. In a similar experiment when lags for public research were increased from 16 to 28, the coefficient for education increased from 0.33 to

0.38. Lag lengths of 20 years for public research and extension and 18 years for private research investments are chosen based on the minimum values of the Schwartz Criterion which gives more consistent tests compared to the Akaike Information Criterion[9].

The results show a significant positive relationship between investments in research and productivity in U.S. agriculture. The Likelihood Ratio test rejects the null hypotheses that the sum of the coefficients is equal to zero for both public and private research expenditures at the 1% level of significance. The significant positive relationship implies positive payoffs to agriculture research.

The productivity elasticity provides an intuitive interpretation of the estimated coefficients[10]. The results in Table 4 indicate that a 1% increase in public research expenditure raises productivity by 0.38%, while a 1% increase in private research raises farm productivity by only 0.17%. We can only speculate why agricultural productivity responds more to public than private research. one possibility is that more of the benefits of private research are captured by the firms doing the research and less of the benefits show up in the multifactor productivity index. The differential response also may arise from differences in the type of research being conducted by each sector. Public agricultural research includes considerable basic research that may have a very high payoff which private firms are unable to appropriate. Private agricultural research emphasizes investments on applied research and development.

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[9] Mills shows that the Akaike information criterion is less consistent relative to the Schwartz criterion, and tends to select an over-parameterized model as the number of data points increase.

[10] Productivity elasticity (e_p) is estimated by using following formula:

$$e_p = \sum_{j=0}^{m} \frac{\partial MFP_t}{\partial R_{t-j}} \frac{R_{t-j}}{MFP_t} \quad \text{where R = PRE, PRD, and EDU.}$$

Results show that the education level of farm operators has a significant positive impact on farm productivity. Skills acquired from schooling improve farmers' ability to process information and select, manage, and operate new technologies. The cointegration model estimates that one additional year of education for farm operators raises farm productivity by about 0.32% in the long-run[11].

Factor terms of trade, defined as real prices received by farmers for crops and livestock per unit of production input, also plays a significant role in enhancing farm productivity. If terms of trade are favorable, farmers have greater financial means and incentive to purchase technologically improved inputs that raise productivity of agriculture. Each 1% increase in factor terms of trade raises farm productivity by 0.16% in the long-run.

The error correction model indicates that government commodity programs represented by excess production capacity are not a significant factor in improving farm productivity. This result is contrary to the findings of Huffman and Evenson (1993, p.208) and Makki and Tweeten that indicate a significant positive relationship between government programs and agricultural productivity. Those studies, however, base their conclusions on a time series model which does not account for the data nonstationarity and cointegration between the two variables.

Internal Rate of Return

The internal rate of return (IRR), defined as the discount rate that makes the net present value of research investments equal to zero, was calculated using the stream of marginal products obtained from the error correction model (Davis). The procedure is implemented by solving the following equation for the internal rate of return:

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[11] Huffman and Evenson (1993, p.755) report a even higher productivity elasticity (0.837) for farmers' schooling using Zellner's Seemingly Unrelated Regression method for years 1950 through 1982.

$$IRR = r : \sum VMP_j(1+r)^{-j} - 1.0 = 0.0 \tag{9}$$

where the value marginal product VMP_j is the marginal physical product of agriculture research after j periods times the output price, and r is the interest rate.

After appropriately accounting for the nonstationarity in the original variables and specifying the equilibrium condition as a cointegrated ECM, we estimate the IRR as 27% for public R&E and as 6% for private R&D (Table 5). These rates of return are lower than IRRs reported by Makki and Tweeten for the same data set but using the polynomial distributed lag procedure without correcting for data nonstationarity.

Our calculated rates of return are lower for private research than for public research, but still comparable to current market rates of return on treasury bills (7%) and corporate bonds (8%). Chavas and Cox report a much higher rate of return of 17% to private research (Table

Table 5. Internal Rates of Return to Public and Private Investments to Raise Productivity of American Agriculture (in %)

Study	Time Period	Public R&E	Private R&D	Estimation procedure
Present Study (1995)	1930-1990	27	6	Cointegration/ECM
Yee (1995)	1931-1985	49	a	Polynomial distributed Lag
Makki and Tweeten (1993)	1930-1990	93	45	Polynomial distributed Lag
Huffman and Evenson (1993)	1950-1982	41	46	Zellner's SUR
Chavas and Cox (1992)	1950-1982	28	17	Non parametric
Huffman and Evenson (1989)	1949-1974	62	0[b]	Zellner's SUR
Braha and Tweeten (1986)	1939-1982	50	a	Polynomial distributed Lag
Davis (1981)	1964-1974	28-52	a	Polynomial distributed Lag
Knutson and Tweeten (1979)	1969-1972	28-35	a	Polynomial distributed Lag
Cline (1975)	1939-1972	41-50	a	Polynomial distributed Lag
Griliches (1964)	1949-1959	300	a	Production Function

a. No estimates available.

b. Estimates were slightly negative or near zero.

5). Their estimate may have been inflated by not controlling for education. Private research and farmers' schooling are highly correlated in levels. With schooling omitted, our estimated internal rate of return for private research was 11 percent. However, analysts using other methods but controlling for education found even higher rates of return on private R&D (Huffman and Evenson, 1993; Makki and Tweeten).

Conclusions

Our research indicates a significant positive relationship between agricultural productivity and public and private investments in research and extension. The estimated internal rates of return are 27% for public research and 6% for private research. The empirical findings of this study illustrate the usefulness of the cointegration approach in explaining the relationship between agricultural productivity and research investments in agriculture. The results also demonstrate the importance of correcting for trend and nonstationarity in measuring economic returns to agriculture research.

Although rates of return to public research and extension are lower than found in previous studies not employing an error correction model, the estimated long-term rate of returns are favorable compared to returns on alternative investments and high enough to justify continued public investments to raise agricultural productivity. In addition, public research, especially basic research, can improve conditions for applied private research by supplying scientific breakthroughs. The economic incentive for private research will be reduced without adequate investment in basic research. On the contrary, commodity programs have little effect on improving U.S. farm productivity. Given these findings, it appears that the interest of U.S. agriculture would be better served by focussing on research, extension, and education, which have greater potential to positively impact upon agriculture performance. Policy debate to reduce public spending on agricultural research and extension should carefully consider the potential long-term implications of such a policy.

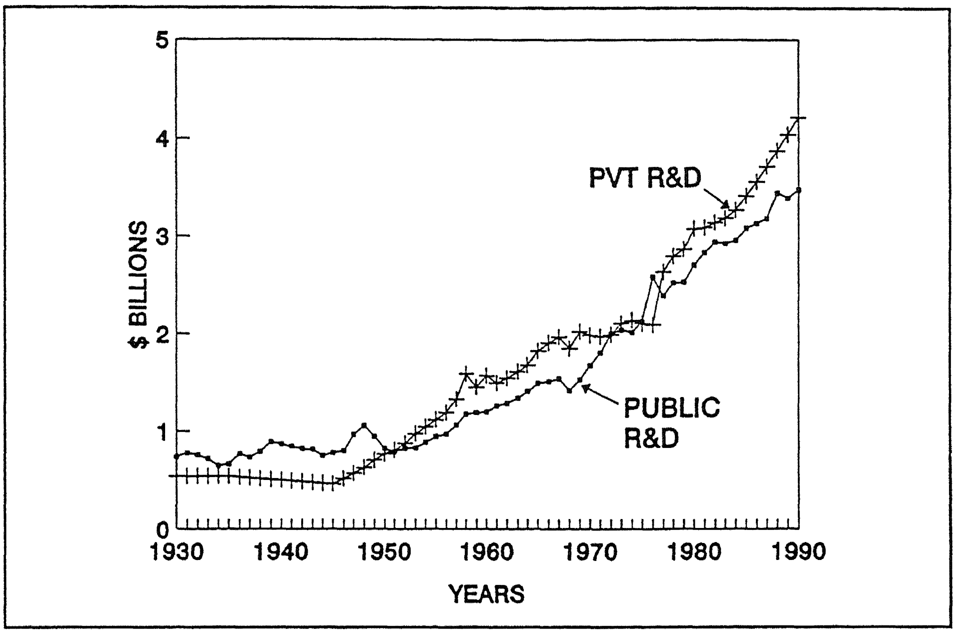

Figure 1. Public and Private Investments in Agricultural Research and Extension in the US, 1930-1990

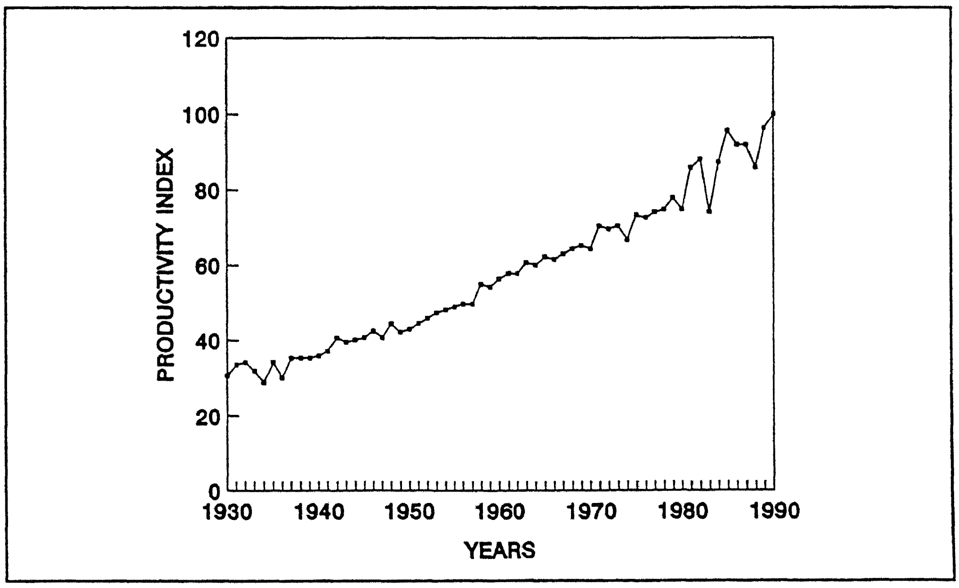

Figure 2. US Agricultural Productivity, 1930-1990

Appendix A

Autocorrelation and Partial Autocorrelation Functions

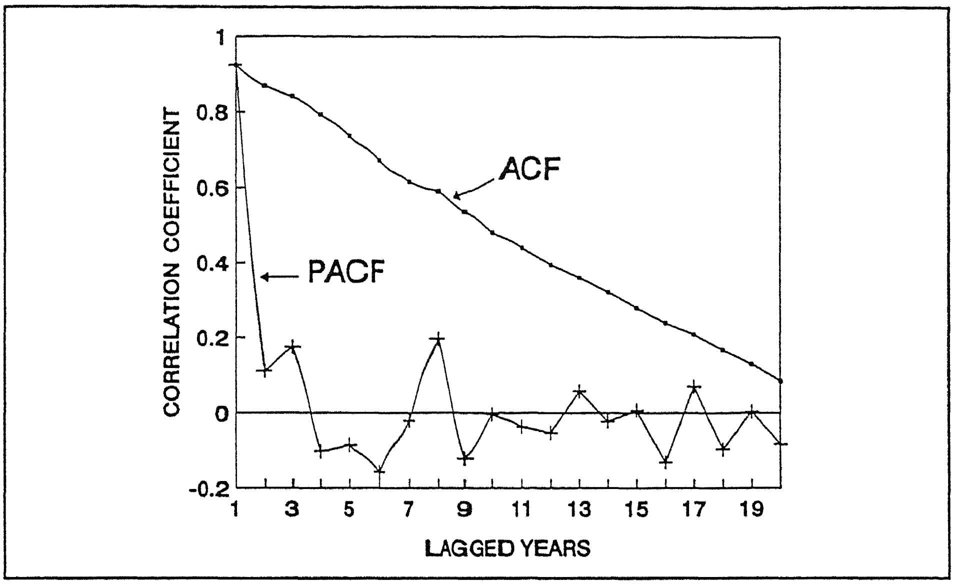

Figure A1. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) for Productivity Index

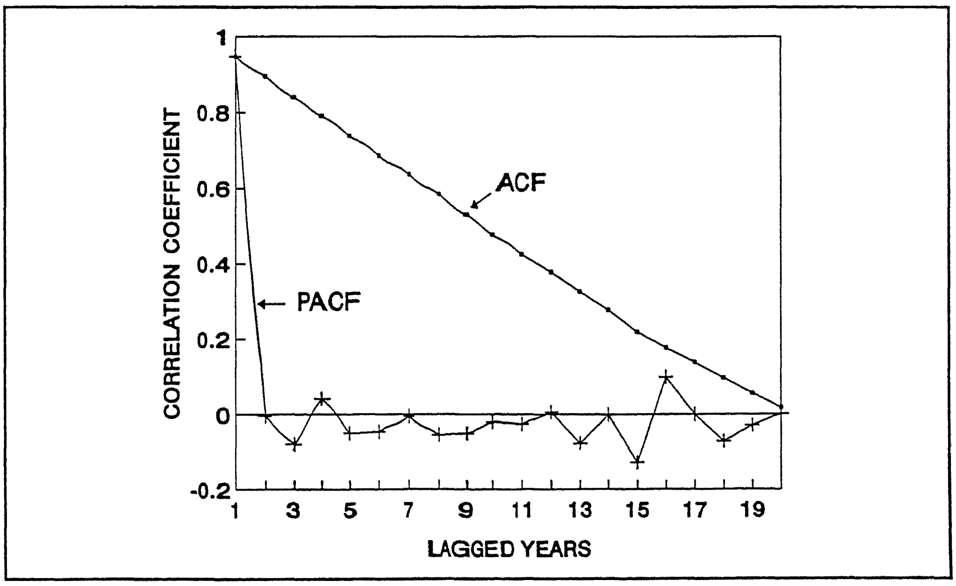

Figure A2. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) for Public R&E Investments

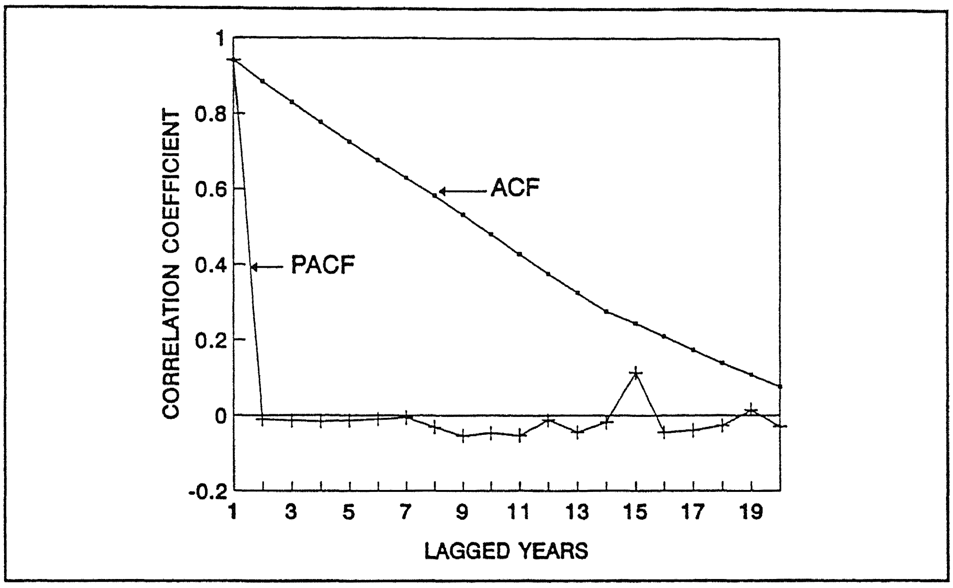

Figure A3. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) for Private R&D Investments

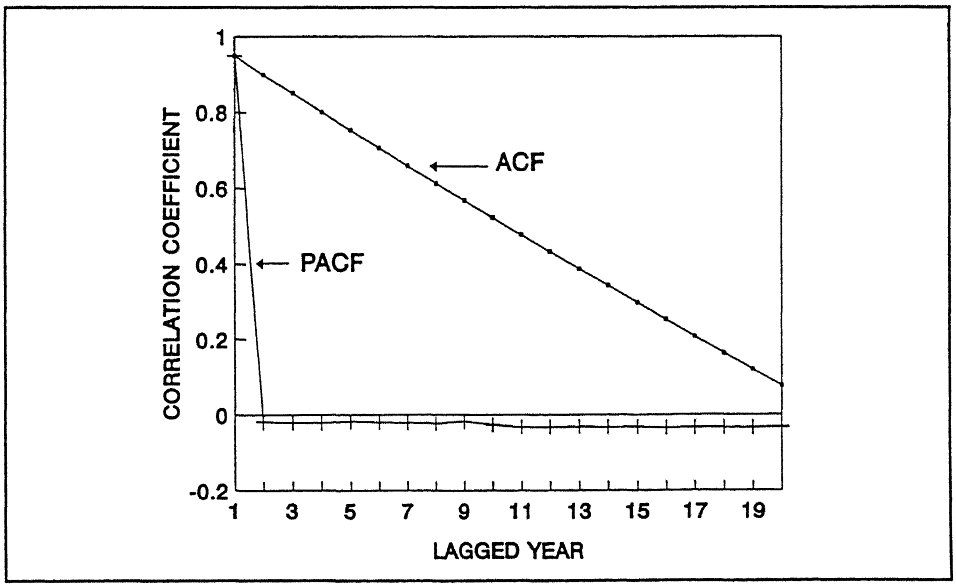

Figure A4. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) for Farmer's Schooling Index

Appendix B

A Note on Causality

Cointegration says nothing about the direction of the causal relationship among the variables. A common problem in economics is determining whether changes in one variable are a cause of changes in another. For example, changes in R&D cause changes in productivity as assumed in this study, or productivity and R&D are both simultaneously determined causing fundamental identification problem in equation (8). A consistent estimation of (8) is possible if we can rule out simultaneity of the relationship. To test causality, if any, we applied the *Hausman specification test* and the *Granger causality test* (Pindyck and Rubinfeld).

1. Hausman Specification Test

The test in the context of productivity and R&D relationship in the cointegration model (8) is formulated in two steps. First step involves specifying a reduced form equation for R&D by regressing R&D on all exogenous variables, which yields

$$\text{(A.1)} \qquad \Delta R\&D_t = A + \sum_{i=1}^{m} \theta_i \, \Delta R\&D_{t-i} + \pi \Delta X + e_t \, ,$$

where $R\&D_t$ is the sum of public and private research investments, and X is a vector of other exogenous variables that affect productivity and research expenditures: education, factor terms of trade, commodity programs, and weather factors.

In the second step, we use the residuals from (A.1) in estimating the following regression equation:

$$\text{(A.2)} \qquad \Delta MFP_t = B + \sum_{i=0}^{m} \xi_i \, \Delta R\&D_{t-i} + \lambda \hat{e}_t + \epsilon_t \, .$$

Under the null hypothesis of no simultaneity MFP_t and e_t are uncorrelated, and thus the coefficient λ should equal zero. See Pindyck and Rubinfeld for more details on this test.

2. Granger Causality Test

Granger's causality test involves two regression functions. First, productivity is regressed on lagged values of itself and research investments, and other relevant exogenous variables. The second equation involves a similar regression with research investments as dependent variable.

(A.3) $$\Delta MFP_t = A + \sum_{i=1}^{n} \alpha_j \, \Delta MFP_{t-j} + \sum_{i=0}^{m} \beta_i \, \Delta R\&D_{t-i} + \gamma \Delta X + u_t$$

(A.4) $$\Delta R\&D_t = B + \sum_{j=0}^{n} \varphi_j \, \Delta MFP_{t-j} + \sum_{i=1}^{m} \psi_i \, \Delta R\&D_{t-i} + \Gamma \Delta X + v_t$$

For there to be unidirectional causality from $R\&D_t$ to MFP_t, the estimated coefficients of lagged $R\&D_t$ in (A.3) should be significantly different from zero as a group ($\sum_{i=0}^{m} \beta_i \neq 0$) and the sum of the coefficients on lagged MFP_t should not be significantly different from zero ($\sum_{j=1}^{n} \alpha_j = 0$). Bilateral causality is suggested when both $\sum_{i=0}^{m} \beta_i \neq 0$ in (A.3) and $\sum_{j=0}^{n} \varphi_j \neq 0$ in (A.4), and independence when they are not significantly different from zero.

Both the Hausman specification test and the Granger causality test do not reject the null of no simultaneity in the relationship between productivity and research investments (Table A). We conclude that the causality is unidirectional from research investments to productivity and not vice versa.

Table A. Testing Causality: Results from Hausman specification test and Granger causality test.

1. Hausman Specification Test

(A.1) $R\&D_t = -239.34 + 0.5805\ R\&D_{t-i} - 0.5086\ EDU_t - 1.2123\ FTT_t - 35.59\ EPC_t + 2.9518\ WRF_t$
[-0.39] [0.64] [-0.09] [-0.27] [-0.73] [0.51]

(A.2) $MFP_t = 1.0558 + 0.0129\ R\&D_{t-i} + 0.0019\ e_t$
[0.51] [0.57] [0.05]

2. Granger Causality Test

(A.3) $MFP_t = -19.53 - 1.044\ MFP_{t-j} + 0.036\ R\&D_{t-i} + 1.029\ EDU_t + 0.076\ FTT_t + 2.88\ EPC_t + 0.19\ WRF_t$
[-1.94] [-1.18] [2.05] [0.93] [0.99] [3.80] [2.00]

(A.4) $R\&D_t = 265.24 + 6.460\ MFP_{t-j} - 0.298\ R\&D_{t-i} - 80.724\ EDU_t + 0.08\ FTT_t - 89.8\ EPC_t - 1.1219\ WRF_t$
[0.31] [0.08] [-0.20] [-1.03] [0.01] [-1.09] [-0.13]

Notes: a. Figures in the parentheses are t values
b. All variables are in first differences except WRF_t and e_t
c. The coefficients for $R\&D_t$ and MFP_t are sum of 20 and 6 lagged coefficients, respectively.

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